CENTER FOR DECISION RESEARCH

Ambiguity and Competitive Decision Making: Some Implications and Tests

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Contrary to most formal models of decision making under risk and uncertainty that are built on the basis of *prescriptive* behavioral principles or axioms, this paper derives a *descriptive* model of decision making under ambiguity based on principles of behavior, i.e., principles that describe *how* people behave as opposed to how they *should* behave. The model assumes that people evaluate the impact of ambiguous probabilities by first anchoring on a given value of the unknown probability and then adjusting this by the net effect of imagining or "trying out" other values the probability could take. The mental simulation process incorporates giving differential weight to the ranges of probability values above and below the anchor where such weight reflects individual and situational variables. In particular, the assumption that people are cautious as opposed to reckless in making decisions, leads to attributing more weight to possible values of probabilities below the anchor when considering potential gains, and the reverse when faced with potential losses. Although the model is derived making general functional statements, it

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Ambiguity in competitive decision making:

Some implications and tests

As attested by the existence of this volume, interest in models of decision making under risk and uncertainty has increased dramatically over the last decade. In the midst of this activity, it is appropriate to ask how this research will be evaluated by future generations. Two probable criteria center on the descriptive and prescriptive aspects of decision making. First, do we understand better *how* people make decisions? Second, to what extent has this work led to improving our understanding of *how to* make decisions? This paper is a contribution to the former question and is motivated by the following concern.

Much work to date has been fueled by a limited number of robust, experimental findings that indicate violations of the norms of expected utility theory (von Neumann & Morgenstern, 1947) and/or subjectively expected utility theory (Savage, 1954). Typically, investigators have concentrated on a few behavioral paradoxes or anomalies, such as those first investigated by Allais (1953) and Ellsberg (1961), and then sought to see how these can be accommodated by relaxing or reformulating certain axioms (for an instructive overview of different approaches, see Weber & Camerer, 1987). However, although a research strategy that involves generalizing existing models to account for anomalous observations has been fruitfully employed in many areas of science, it is questionable whether this strategy will ultimately prove successful in developing good *descriptive* models of *how* people make decisions. There are at least three reasons.

First, whereas the axioms underlying expected (and subjectively expected) utility theory are sometimes referred to as "behavioral," this term is misleading. On the one hand, it is true that the axioms are behavioral in the sense that they provide "behavioral principles" (such as transitivity of preferences) that most people would want to follow in making decisions. On the other hand, these axioms are not "principles of behavior" in the sense that they provide descriptions of the

underlying laws or processes that govern behavior. To illustrate, consider the difference between the principle of transitivity and the Weber-Fechner law. The former is a *behavioral principle* to which most people adhere even though it is violated, on occasion, in actual choices (cf. Tversky, 1969). The latter is a *principle of behavior* that describes the relation between the subjective evaluation of a stimulus and its objective measurement. Moreover, this can lead to undesirable behavior such as when the value of an object differs depending on the basis used for comparison (e.g., a discount of $5 seems more valuable when paired with a $15 as opposed to a $100 purchase even though $5 is $5 is $5.... See Thaler, 1980). In my view, the elements on which descriptive models of decision making should be based are principles of behavior, not behavioral principles. In other words, descriptive models should be built on descriptive principles (cf. Tversky & Kahneman, 1986).[1]

Second, a striking feature of the literature on behavioral anomalies is that a large majority of studies have examined precisely the same "paradoxes" using almost exactly the same stimuli with little or no parametric variations (for an exception, see MacCrimmon & Larsson, 1979). Thus, whereas the different generalized expected utility models may account for (i.e., are compatible with) some of the classic paradoxes, it is not clear what other phenomena they illuminate. In an important sense, the phenomena have become overdetermined; there are too many models chasing too few phenomena.

Third, situations involving risky choices have been primarily represented in the form of gambles, an abstraction that has proved fruitful in understanding the canonical structure of risky decision making. However, to what extent do people experience risky decisions as explicit gambles? What is the range of circumstances to which the gambling analogy applies (cf. Lopes, 1983)? Much experimental work on risk is reminiscent of early attempts in psychology to study memory by requiring subjects to learn lists of nonsense syllables. Although useful in some limited respects, this paradigm failed to illuminate processes of long-term memory which are considerably

facilitated, if not dependent on substantive content. In other words, since content conditions much of human experience, models that abstract from content are necessarily limited in application.

In this paper, I respond to these limitations of existing work by presenting a model of decision making under ambiguity that is tested in two experiments embedded in substantive contexts. The paper is organized as follows. First, I state the principles of behavior underlying the model and show how these are compatible with the ambiguity model developed by Einhorn and Hogarth (1985; 1986). Second, implications of the model are derived and tested in two experiments in which "gambles" are presented within the context of two competitive decision making situations: one concerning legal decision making, the other the purchase and sale of industrial equipment. Finally, I discuss the results of these experiments, how the model differs from others proposed in the literature, and implications for future work.

The ambiguity model

Although the probabilities associated with payoffs are explicitly stated in most laboratory experiments on risk, information concerning probabilities is often ambiguous in naturally occurring situations. Thus, it is important to model and understand how people process and evaluate information concerning ambiguous probabilities. To do so, I first define what I mean by ambiguity.

The meaning of ambiguity. Ambiguity refers to uncertainty about one's degree of uncertainty. In this paper, the probability of an event is defined as ambiguous if one lacks information that would allow one to attribute a unique value to it.[2] In addition, the more alternative values that can be attributed to the probability of the event, the more ambiguous it is (see Einhorn & Hogarth, 1985, p.435). Following this definition, it is important to note that ambiguity cannot be equated with all forms of "second-order" uncertainty (Marschak, 1975). For example, some researchers (e.g., Camerer & Kunreuther, 1988) have operationalized ambiguity by means of

two-stage gambles. In this paradigm, subjects are confronted with, say, two random devices (e.g., bingo cages or urns) involving different but known probability distributions. They are informed that the outcome of interest will result from a drawing made from one of the devices chosen at random (by, for example, using a fair coin). However, the choice of device is not revealed to them. At first sight, this might seem to operationalize an ambiguous situation in that, from the subject's viewpoint, there is uncertainty concerning the probability distribution that will determine the outcome. However, if the probabilities of choosing the random devices are known to the subject, the situation is not ambiguous since the probability of observing the event of interest can be precisely calculated.

Psychological assumptions. The general assumption underlying the model is that subjective weights given to ambiguous probabilities are the end result of an anchoring-and-adjustment process (cf.Tversky & Kahneman, 1974; Einhorn & Hogarth, 1985). People are assumed to anchor on a particular estimate of the probability and then adjust this by imagining, via a mental simulation process, other values that the probability could take. To illustrate, consider a situation in which you are concerned about the chances of an accident occurring in a new industrial facility. Although a study conducted by technical experts assesses the risk as $p = .001$, you have some doubts about the precision of this estimate. In the process assumed here, it is postulated that you would first anchor on a given value of probability (e.g., the .001 provided by the experts) and then imagine or "try out" other values the probability could take, both below and above the anchor. Depending on the circumstances (see below), you would not necessarily accord equal weight in imagination to possible values of the probabilities on both sides of the anchor. For instance, in the present example values above the anchor may well weigh more heavily in imagination than those below (the occurrence of accidents might be salient). The resulting weight given to the ambiguous probability is taken to reflect both the initial anchor and the *net* effect of the mental simulation process and can be written

$$S(p_A) = p_A + (k_g - k_s) \qquad (1)$$

where p_A is the anchor, k_g represents the values and weight accorded in the mental simulation to values of p greater than the anchor, and k_s corresponds to the weighted values below the anchor.

To make these notions operational in terms of principles of behavior, one needs to specify (1) how the anchor, p_A, is established, (2) what affects the *amount* of mental simulation (i.e.,the ranges of alternative probability values considered), and (3) what determines the *sign* or direction of the adjustment process.

(1) In ambiguous circumstances, it is assumed that some initial value of the probability is typically available to the decision maker. This may be a figure based on historical data, provided by experts (as in the example above), or selected from memory.

(2) In considering the amount of mental simulation, compare situations where there is alternatively no and considerable ambiguity. In the former, the decision maker has sufficient knowledge to assign a unique value to the probability such that there would be little or no mental simulation (however, see, Hogarth & Einhorn, 1988). In the latter, one would expect considerable simulation, the extent of which is assumed to be positively related to the amount of perceived ambiguity. In other words, the more alternative values that cannot be eliminated by the decision maker's knowledge concerning the probability of the event, the greater the extent of mental simulation. (Recall the definition of ambiguity given above).

(3) The sign, or net effect of the adjustment process (i.e., $k_g - k_s$), reflects two factors. These are (a) the location of p_A, and (b) the relative weight given to imagined values of the probability above and below the anchor. The location of p_A affects the net effect of the adjustment process in that, if $p_A = 0$, the adjustment must be positive, and negative if $p_A = 1$. It also follows that for small values of p_A there is a greater range of values of the probability that can be imagined

above the anchor than below it; for large values of p_A, it is the reverse.

A critical feature of the model concerns the weighting of values of the probability above and below the anchor. This is taken to reflect two factors. First, it is reasonable to assume individual differences. Thus, when assessing the impact of ambiguous probabilistic information on the chances of obtaining a good outcome (e.g., a large sum of money), people may differ in the extent to which they imagine values above and below the anchor. Indeed, evidence of such stable differences can be found in data reported by Einhorn and Hogarth (1985). Second, differential weight also reflects the context in which probabilities are assessed. Specifically, it is assumed that people are cautious rather than reckless when taking decisions under uncertainty (see, e.g., the literature on "defensive pessimism," Norem & Cantor, 1986a; 1986b). It therefore follows that for decisions involving good or positive payoffs, values greater than the anchor are underweighted relative to those below. Conversely, bad or negative payoffs imply that greater weight is accorded to values of probability above rather than below the anchor. Moreover, the absolute size of payoffs is also assumed to affect imagination. This means that, for positive payoffs, more weight is given to possible values of the probability below the anchor as payoffs increase whereas, for negative payoffs, the larger the stakes the more weight is given to values above the anchor.

The assumptions concerning the sign and size of the adjustment in equation 1, i.e., $(k_g - k_s)$, can be summarized by writing

$$k_g = f(\theta, p_A, \rho) \tag{2a}$$

and

$$k_s = g(\theta, p_A, \lambda) \tag{2b}$$

where both k_g and k_s are increasing functions of perceived ambiguity defined by the parameter θ, k_g is a decreasing function of p_A but k_s is an increasing function of p_A, and ρ and λ are

parameters representing the weight given in imagination to values of probabilities above and below the anchor, respectively. (As also implied above, ρ and λ are increasing functions of the absolute sizes of payoffs).

Further specifications. Since the above functions are loosely specified, some restrictions are imposed that correspond with the underlying psychological intuitions. First, consider the $S(p_A)$ values associated with anchors of 0 and 1. In the presence of ambiguity, these are adjusted, up for $p_A = 0$, and down for $p_A = 1$. Moreover, the amount of the adjustment reflects the degree of perceived ambiguity. (A thought experiment: Would you prefer having a "known zero" chance of winning a prize as opposed to an "ambiguous zero" chance?) In the interest of symmetry, assume that the amount by which $S(p_A)$ overweights p_A when $p_A = 0$ is the same as the amount of underweighting when $p_A = 1$.

Second, consider a situation where $p_A = .5$ and probability values above and below the anchor are weighted equally in imagination. In this case, it seems reasonable to assume that $S(p_A) = .5$ since, in addition to equal weighting, the ranges of possible values of the probability above and below the anchor are the same. Thus when equal weight is given to values imagined above and below the anchor, the function relating $S(p_A)$ to p_A will be such that $S(p_A) > p_A$ for $p_A = 0$, $S(p_A) = p_A$ for $p_A = .5$, and $S(p_A) < p_A$ for $p_A = 1$. In fact, the three values of $S(p_A)$ corresponding to $p_A = 0, .5$, and 1 can be connected by a straight line as illustrated in Figure 1a.

Insert Figure 1 about here

This special case of the "ambiguity function" provides insight into its general shape; small probabilities are overweighted relative to their anchors, and large probabilities underweighted.

Now consider the case where $p_A = .5$ and values below the anchor are weighted more heavily in imagination than those above. Here $S(p_A) < p_A$ since although the ranges of possible

values on both sides of the anchor are equal, those below are weighted more heavily. However, there will be a point between $p_A = 0$ and $p_A = .5$ where $S(p_A) = p_A$. This point, labeled p_c (to denote "cross over") occurs when the additional weight given to values below the anchor (relative to those above) exactly compensates for the fact that the range of possible values below the anchor is smaller than that above. It also follows that this cross-over point will be closer to $p_A = 0$ the more weight is accorded to values below the anchor than above. Figure 1b shows the extrapolation of this reasoning in graphical form. Following analogous arguments, Figure lc shows that the cross-over point must occur above $p_A = .5$ if values above the anchor are weighted more heavily in imagination than those below.

Whereas the ambiguity functions may take several forms, it is reasonable to restrict them in two ways. First, there is a unique cross-over point; second, for $0 \leq p_c < .5$ and $.5 < p_c \leq 1$ the $S(p_A)$ values of complementary anchors, i.e., p_A and $(1-p_A)$, do not sum to 1. For the former, $S(p_A) + S(1-p_A) < 1$; for the latter, $S(p_A) + S(1-p_A) > 1$. Although these are not severe restrictions on functional forms, they are important in that, as noted by many scholars, Ellsberg's (1961) paradox can be explained by models that imply nonadditive probabilities (for a review, see Fishburn, 1986).

Implications. There are several implications of the model as defined above. First, note that the "ambiguity function" is regressive with respect to p_A. In general, the function starts by "overweighting," has a cross-over point (p_c), and then "underweights" the anchor. The location of the cross-over point depends on the relative weight given in imagination to values of the probability above and below the anchor.

Second, the extent to which $S(p_A)$ deviates from p_A over the range of the latter depends on the amount of perceived ambiguity, i.e., the greater perceived ambiguity (and hence mental simulation), the greater the deviation.

Third, except for cases where $p_A = 0$ or 1 or $p_c = .5$, $S(p_A)$ values are subadditive when

decision makers are confronted with gains, but superadditive in the face of losses.

Fourth, since Figure 1b represents the ambiguity function of someone facing positive payoffs, and Figure 1c corresponds to a situation of negative payoffs, one can make general qualitative statements concerning attitudes toward ambiguity, i.e., whether people prefer to make choices determined by ambiguous probabilities anchored on p_A as opposed to precise probabilities equal to p_A. Note, from Figure 1b, that the general tendency is to avoid ambiguity in the case of gains over most of the range of p_A except when this is small. Conversely, for losses, the general tendency is to avoid ambiguity over most of the range of p_A but to seek ambiguity when the probability of loss is high.

Finally, the model predicts values of p_A for which the distinction between ambiguous and non-ambiguous probabilities is negligible. These occur in the region around p_c, the precise location of which depends, as noted above, on factors that affect the relative weighting in imagination of probabilities above and below the anchor (e.g., sign of payoffs). Thus choices involving anchor probabilities in the region of p_c are predicted to be insensitive to the effects of ambiguity.

A specific functional form There are several ways in which the model could be represented by specific functions. A simple, and direct representation is that adopted by Einhorn and Hogarth (1985; 1986).

First, let k_g and k_s be proportional to $(1-p_A)$ and p_A, respectively, where the constant of proportionality is θ, perceived ambiguity ($0 \leq \theta \leq 1$). To model the allocation of differential weight in imagination to values of the probability above and below the anchor, note that the adjustment in equation 1 is equal to the difference between k_g and k_s. From a mathematical viewpoint, this means that a single parameter can be used to capture the joint effects of ρ and λ in equations 2a and 2b. For convenience[3], this is done by raising p_A in k_s to a power β ($\beta \geq 0$) such that k_g and k_s can be written

$$k_g = \theta (1 - p_A) \tag{3a}$$

and

$$k_s = \theta p_A^{\beta} \tag{3b}$$

When equations 3a and 3b are substituted into equation 1, the model can be expressed as

$$S(p_A) = p_A + \theta (1 - p_A - p_A^{\beta}) \tag{4}$$

Einhorn and Hogarth (1985; 1986) refer to β as representing the decision maker's "attitude toward ambiguity in the circumstances." Its specific values can be mapped into the substantive assumptions discussed above as follows. When $\beta = 1$, equal weight is given in imagination to values of the probability above and below the anchor; for $0 \leq \beta < 1$, more weight is given to values below the anchor; and for $\beta > 1$, more weight is given to values above the anchor. Thus, when faced with uncertainties involving gains, $\beta < 1$ -- see Figure 1b. When faced with losses, $\beta > 1$ -- see Figure 1c. More generally, greater caution in the domain of gains is associated with smaller values of β; however, greater caution in the domain of losses is associated with larger values of β.

Experimental evidence

Equation 4 has already been tested in a variety of experimental studies involving problems in inference, gambles with urns, and scenarios involving the purchase and sale of insurance and warranties. Moreover, these studies have been conducted with subjects having different levels of substantive expertise, e.g., professional actuaries, business executives, MBA students, and

undergraduates. (See Einhorn & Hogarth, 1985; 1986; 1988; Hogarth & Kunreuther 1985; in press; 1988). The intention of the experiments reported in this paper is to explore how ambiguity affects competitive situations by having differential impacts on opposing parties. In particular, does asymmetry in the manner in which ambiguity affects the two sides of a decision or transaction confer competitive advantages on one of the parties? There are two experiments. One deals with a legal decision making situation, the other with the purchase and sale of industrial equipment.

Experiment 1

Rationale. Imagine a case of civil litigation where both plaintiff and defendant must decide whether to accept an out-of-court settlement or risk going to court. For the plaintiff, this decision is naturally framed as either accepting a sure sum (the settlement) or going to court with the possibility of gaining a larger sum or losing all. For the defendant, it is the reverse: either lose money for sure (the settlement) or go to court with the chance of losing either more or nothing. To continue the example, imagine that the two parties agree on both the probability that the plaintiff will win the case and the amount that each is prepared to pay the other to settle out of court. Assume further that this amount is equal to the expected value at stake in the court case. Ignoring consideration of legal costs, what actions do different choice theories predict would be taken by plaintiff and defendant?

An expected utility analysis predicts that, provided the plaintiff and the defendant are risk-averse and agree on the probability of the outcome of the case, they will both prefer to settle out of court (Gould, 1973).[4] This contrasts with prospect theory (Kahneman & Tversky, 1979) which makes differential predictions due (principally) to the contrasting shapes of the value function over losses and gains. These predictions are that the plaintiff, whose situation is framed in terms of gains, will take the risk-averse action (i.e., settle out of court) provided the probability of winning the case is not very small; the defendant, however, whose situation is framed in terms of

losses, will take the risky action (i.e., go to court). And indeed, the prospect theory predictions have been upheld in experimental tests of this legal decision making situation (Hogarth, 1987, Ch.5).

However, what happens if probabilities are ambiguous? First, note that neither expected utility theory nor prospect theory make specific predictions concerning the effects of ambiguity. Second, since the $S(p_A)$ values from the ambiguity model are, in effect, decision weights, it is illuminating to predict the effects of ambiguity by substituting these values for the prospect theory decision weights. This leads to the following predictions. (1) For plaintiffs, when probabilities of winning the case are moderate or large, ambiguity implies underweighting the anchor probabilities (see Figure 1b) thereby reinforcing the choice to settle out of court. In other words, under ambiguity plaintiffs will be more likely to choose the riskless option (i.e., settle out of court) than when probabilities are not ambiguous. (2) For defendants, the predictions are more complex. For high probability of loss events, ambiguous probabilities are underweighted relative to their anchors (see Figure 1c) such that defendants would be expected to continue to take the risky option (go to court). Indeed, for high probability of loss events the model predicts greater risk seeking under ambiguity when probabilities are ambiguous as opposed to non-ambiguous. However, in the presence of ambiguity, the tendency to take the risky alternative will be reduced, relative to the non-ambiguous case, as the probability of losing the case decreases. This prediction follows from the implication that, for losses, there is overweighting of anchor probabilities when these are small or moderate (see Figure 1c) thereby counteracting the tendency toward risk seeking over losses predicted by prospect theory. To summarize, defendants are predicted to exhibit risk-seeking behavior at high probability of loss levels irrespective of ambiguity. At moderate probability levels, however, defendants with ambiguous information about probabilities will exhibit more risk-averse behavior than those with precise probability estimates. The following experiment was designed to test these predictions.

Subjects. Subjects were 80 MBA students at the University of Chicago taking a course in decision making taught by the author. As assignments given in the first and second weeks of the course, students were required to complete two questionnaires which contained several decision making problems that were to be debriefed and discussed later in the course.

Task and method. Subjects were allocated at random to four experimental conditions that were created by crossing two kinds of role (plaintiff or defendant) by two types of probabilistic information (ambiguous or non-ambiguous). In addition, two levels of probability were varied as a within-subject factor by setting the probability of the plaintiff winning the trial at .80 in the first questionnaire, and at .50 in the second which was completed one week later.

The stimulus consisted of a short scenario which stated: whether the subject was the plaintiff or defendant; the amount at stake in the case (subjects were asked to imagine that this was $20,000 of their own money); an estimate by the party's lawyer of the probability that the case would be won by the plaintiff (see below); and knowledge supplied by each party's lawyer that the opposing party would settle for a given sum (minimum for the plaintiff, maximum for the defendant). This sum was $16,000 in the .80 probability condition, and $10,000 in the .50 condition. The scenario made no mention of the reasons underlying the litigation and subjects were instructed to ignore legal costs. Subjects were required to decide between accepting the out-of-court settlement (i.e., $16,000 or $10,000) or to risk going to court.

Ambiguity was manipulated in the scenarios by stating, in the ambiguous case, that in response to a query about the chances of winning or losing the case, the lawyer gave a best guess "after some hesitation" and that "given the nature of the case, he feels very uneasy about providing you with such a figure." In contrast, the non-ambiguous version simply stated "your lawyer believes there is a .... chance that..."

Results. Table 1 summarizes results of the experiment by reporting the percentages of subjects choosing to settle out of court in each experimental condition. Recall first that, for

plaintiffs, the model predicts that ambiguity will act as a force toward risk aversion. For defendants, on the other hand, ambiguity is only expected to induce risk-averse behavior at low or moderate probability levels, e.g., at .50 but not at .80.

Results show that at the .80 probability level, the vast majority of plaintiffs chose to settle out of court, whereas most defendants took the risky option of going to court. Moreover, there are no differences in responses due to ambiguity, 89% versus 96% for the plaintiffs, and 25% versus 10% for the defendants. However, note that in the non-ambiguous condition, since almost all plaintiffs chose the riskless option and most defendants the risky option, choices could not be sensitive to effects of ambiguity.

At the .50 probability level, the pattern of responses for the plaintiffs is almost identical to that at .80 with, again, no effects for ambiguity. However this is not the case for defendants where

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Insert Table 1 about here

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the difference between the percentages of subjects wishing to settle in the non-ambiguous and ambiguous conditions (6 versus 57) is significant ($\chi^2 = 3.63$, df = 1). In addition, whereas there is no significant difference between responses of the same subjects in the non-ambiguous condition at the .80 and .50 probability levels (25% versus 6%), the difference between responses at the two probability levels in the ambiguous condition (10% versus 57%) is significant (Cochran's test, Q = 10.00, df=1, p = .0016). These results clearly support the predictions of the ambiguity model.

Experiment 2

Rationale. Using the language of the gambling analogy, the preceding experiment examined

situations involving two parties (defendants and plaintiffs) facing pure gambles, i.e., losses or gains. It is therefore also instructive to consider situations where two parties face mixed gambles, i.e., with potential losses *and* gains. Of particular interest are situations where the structure of a transaction is such that ambiguity has differential effects on the evaluations made by the two parties. Specifically, if ambiguity has little effect on the evaluation made by one party, but does affect the other, competitive advantages can accrue to one of the parties.

To explore this possibility, consider situations where two parties are on opposing sides of transactions that can be thought of as involving mixed gambles of the following type.

Party A has: A large probability of a modest gain; and
a small probability of a large loss.

Party B has: A large probability of a modest loss; and
a small probability of a large gain.

To be specific, describe A's gamble as ($2,000, .9; - $8,000, .1) and B's gamble as (- $2,000, .9; $8,000; .1).

To evaluate the effects of ambiguity on the situations faced by A and B, recall that Figure 1b represents a typical ambiguity function for gains, whereas Figure 1c depicts one associated with losses. This implies that, for Party A, an ambiguous .9 chance of gaining $2,000 will be evaluated as less attractive than if the .9 chance were not ambiguous (see Figure 1b); in addition, an ambiguous .1 chance of losing $8,000 will be evaluated as more aversive than a .1 chance that is not ambiguous (see Figure 1c). In other words, the model predicts that the situation faced by Party A is sensitive to the effects of ambiguity. Specifically, since both the loss and gain components of Party A's transaction are affected negatively by ambiguity, Party A will evaluate the potential transaction as less attractive in the presence of ambiguity.

In contrast to the predictions for Party A, the model predicts that Party B will be relatively insensitive to the effects of ambiguity. The reason is that the structure of Party B's transaction is

such that the $S(p_A)$ values associated with the potential loss of $2,000 and the potential gain of $8,000 are liable to be in the regions of their respective cross-over points. To see this, consider Figure 1c for losses and note that for a large probability (.9) of a loss, $S(p_A) \approx p_A$. Similarly, for a small probability (.1) of a gain, note from Figure 1b that $S(p_A) \approx p_A$. To be more precise, the ambiguity model does not make clear predictions for Party B in that it does not specify the exact locations of the cross-over points for losses and gains. However, the net effect of ambiguity on Party B's combination of potential loss and gain implies less sensitivity to ambiguity than Party A. For example, the structure of Party B's transaction could imply contrary forces toward ambiguity, i.e., ambiguity aversion for the gain component and ambiguity seeking for losses. Alternatively, Party B might be ambiguity neutral with respect to one component of the gamble, but not the other; and so on.

To summarize, the model predicts that whereas ambiguity will lead Party A to evaluate the transaction less favorably, it will have less impact on the evaluation made by Party B. The following experiment was designed to test this prediction.

Subjects and procedure. Subjects were managers in life insurance companies who were attending a residential, professional seminar. They were sophisticated in economic matters and were primarily employed in managing investment portfolios. Their median age was 39. The evening prior to attending a lecture on "Perceptions of risk," the managers were asked to complete a questionnaire in booklet form (requiring about 30 minutes), the results of which were to be discussed at the lecture. The task was done on an individual basis with managers submitting their completed questionnaires to the course organizers by a specified time. The task described below was included on a separate page in the experimental booklet. Approximately 160 questionnaires were distributed; usable responses were received from 137 managers.

Task and design. The design of the experiment involved four conditions created by crossing two between-subject factors each with two levels. The factors were role (buyers and sellers, see

below) and ambiguity. The latter was made operational by two versions of the experimental stimuli where the probabilities of the relevant events were given in either ambiguous or non-ambiguous form. Subjects were allocated at random to the four cells of the 2 x 2 design.

The scenario used in this experiment involved the purchase and sale of industrial equipment valued at about $100,000. Buyers had the opportunity of obtaining the equipment from one of two suppliers (Alpha and Beta) who differed in respect of their terms of sale. Alpha's price included a warranty against a specific type of breakdown. Beta did not offer a warranty but was willing to sell at a discount relative to Alpha. The problem was structured so that the buyer was asked to consider Beta's offer as involving a potential gain of $2,000 (the discount) against a potential loss of $8,000, where the latter was the difference between the $10,000 cost of repairing the breakdown (should it occur) and the $2,000 discount.

In the seller version of the questionnaire, subjects were told that although their usual policy was to sell machinery with warranties against specific breakdowns, a customer had requested to forego the warranty for a $2,000 discount. This was described as "a one-shot deal and would have no repercussions on the rest of your business." The net effect of the deal was described as "if you sell the machine with a discount, you are facing a potential loss of $2,000 if no breakdown occurs during the warranty period (i.e., the amount of the discount). However, you also stand to gain $8,000 if a breakdown occurs (i.e., you would save repair costs of $10,000 but allow a discount of $2,000)."

Ambiguity was manipulated in the same manner in both the buyer and seller versions of the scenarios. In the ambiguous case, the machinery being sold was described as being "based on new design principles" and that although there was a "best estimate" of the probability of a breakdown within the warranty period, "you experience considerable uncertainty about this estimate." In the non-ambiguous version, subjects were told that "extensive records" existed concerning the machine's breakdown record and that "you can confidently estimate the probability of a breakdown

occurring within the warranty period." The anchor probability of the breakdown occurring within the warranty period was given as .1 (for both buyers and sellers).

Subjects made two responses to the scenario. Buyers were required to choose between Alpha (i.e., buy with warranty but no discount) or Beta (no warranty but discount). In addition, they were asked to state "the maximum discount they would be prepared to accept to buy the equipment without the warranty." Sellers were asked whether they would sell the machinery "at a discount of $2,000 but with no warranty" or "without the discount but with the warranty." Their second question was "What is the maximum discount you would be prepared to grant if you were to sell the machinery without the warranty?"

Results. Using the gambling metaphor, the buyer faced a situation described by ($2,000, .9; - $8,000, .1) and the seller faced (- $2,000, .9; $8,000, .1). Thus following the rationale given above, whereas the buyer's decision should be sensitive to ambiguity, this is not the case for the

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Insert Table 2 about here

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seller. Table 2 presents the results of the experiment in terms of (a) responses concerning preferences for discounts versus warranties and (b) minimum (for buyers) and maximum (for sellers) amounts that the parties would accept (for buyers) or grant (for sellers) in lieu of a warranty.

Consider first the data in respect of preferences for discounts versus warranties. For buyers, whereas 64% of subjects chose the warranty in the ambiguous condition, the corresponding figure was 32% in the non-ambiguous condition ($\chi^2 = 6.35$, df = 1, $p < .02$). In other words, choices made by buyers were consistent with avoiding ambiguity. For sellers, however, whereas 47% choose the warranty in the ambiguous condition, this figure is 61% in the non-ambiguous condition and the difference is not statistically significant ($\chi^2 = 1.28$, df = 1). To summarize, as predicted

buyers (Party A) were sensitive to ambiguity in this situation whereas sellers (Party B) were not.

Results of the choice data are supported by estimates of minimum (for buyers) and maximum (for sellers) discounts. Median and mean discounts stated by buyers in the ambiguous condition exceed those in the non-ambiguous condition The difference between medians is statistically significant ($p < .05$, one-tailed Mann-Whitney test) although the difference between means is not ($t = 1.39$, $p = .086$, one-tailed test). Differences between the mean and median discounts of sellers in the ambiguous and non-ambiguous conditions are both small and statistically insignificant.

Discussion

Discussion of both the ambiguity model and these results is considered from three viewpoints: (a) the particular experiments; (b) alternative models that can account for effects of ambiguity in decision making; and (c) implications for future work.

The experiments. The experiments demonstrate that ambiguity can have differential effects on the evaluations of alternatives made by two parties to a decision. In Experiment 1, since choices made by plaintiffs at both the .80 and .50 probability levels already exhibited considerable risk aversion, ambiguity had little impact. For defendants, however, ambiguity had the predicted effect of making choices more risk averse for lower probabilities (.50 in this case). In the context of negotiations, implications of asymmetries in the evaluation of losses and gains (Kahneman & Tversky, 1979) have already been noted by several researchers (see, e.g., Bazerman, 1983; Hogarth, 1987, Ch.5). The contribution of the present experiment to show how the "baseline" predictions of prospect theory are modified by the presence of ambiguity. These findings thus provide further insight into bargaining behavior that can be used both descriptively and strategically, i.e., when trying to assess what an opponent might do in a bargaining situation.

The results also imply that ambiguity may, on occasion, facilitate agreement between opposing parties. For moderate sized probabilities (in the region of .5), prospect theory predicts

that opposing parties will take different actions (plaintiffs to settle, defendants to go to court). However, the effect of ambiguity is to moderate the risk seeking tendencies of defendants and thus increase the chances that both parties will wish to settle out of court. Since probabilities associated with the outcomes of civil litigation are typically ambiguous, this may contribute to the fact that the vast majority of civil suits are in fact settled out of court. (For an analysis of this phenomenon from a traditional expected utility viewpoint, see Gould, 1973).

Although the task examined in Experiment 2 concerned two parties involved in the purchase and sale of industrial equipment, the paradigm of two parties being on opposite sides of a mixed gamble has more general application. One area is the market for protective services where people can hedge risks by the use of mixed as opposed to pure gambles. Consider, for example, trading in financial instruments, e.g, stocks, bonds, commodities, futures, options, and portfolio insurance. As shown in Experiment 2, if people put themselves into a situation where they have a large probability of gaining a small amount and a small probability of losing a large amount, ambiguity will impact negatively on the evaluation of their position. However, by taking a position that involves a large probability of losing a small amount accompanied by a small probability of gaining a large amount, the subjective evaluation of the position will not be affected by ambiguity. It should be specifically noted that whereas the former situation is analogous to selling a put or call out of the money, the latter is analogous to buying a put or call out of the money. It would be interesting to ascertain empirically what kinds of traders tend to structure deals for themselves that are more similar to the first or the second type of mixed gamble, and whether this leads to strategic advantages in buying and selling. For example, do individuals who are typically subject to ambiguity tend to buy put or calls, and institutions, who are not affected by ambiguity, sell them?

Alternative models. Several models have been proposed to account for effects of ambiguity and, in particular, choices made by subjects in Ellsberg's (1961) paradoxical urn problem. Both Ellsberg (1961) and Fellner (1961) suggested models in which probabilities are "slanted" to

account for imprecision in their estimation. The basic phenomenon these researchers attempted to explain was that of ambiguity avoidance. As a consequence, neither considered ambiguity seeking although Ellsberg was aware of this possibility (see Becker & Brownson, 1964, pp. 63-64, footnote 4). In later work, Gärdenfors and Sahlin (1982; 1983) also proposed a model that takes into account what they called the epistemic reliability of probability estimates. This lead to proposing a decision rule (entitled the "maximin criterion for expected utilities") that can be used in situations involving nonnegative payoffs and implies ambiguity avoidance. Further work concerning the credibility of probabilities has been reported by both Morris (1986) and Nau (1986).

Also stimulated by the need to account for Ellsberg's urn problems, several axiomatic nonadditive probability models have been proposed in which axioms used by Savage (1954) and other researchers in the "personalistic" tradition have been relaxed or weakened. These new formulations include models by Fishburn (1983) and Schmeidler (1984) (for an overview, see Fishburn , 1986). In addition, by relaxing von Neumann and Morgenstern's (1947) reduction-of-compound-lotteries axiom, Segal (1987) has shown how he "anticipated" utility theory of Quiggin (1982; see also Yaari, 1987) can account for both ambiguity avoidance and preference. However, Segal's theory requires one to operationalize ambiguity by means of explicit 2-stage lotteries such that the precise value of an "ambiguous" probability can be calculated. This means, therefore, that Segal's model does not account for probabilities that are ambiguous in the sense defined in this paper.

Two further models are similar to the Einhorn-Hogarth formulation in that they posit effects on "probability functions" that reflect the size or sign of payoffs. One is a model by Hazen (1987) which explicitly includes the notion that the effect of ambiguity is a function of the size of payoffs that are contingent on the occurrence of the uncertain event. The second is the work by Luce and Narens (1985) on "dual bilinear utility" which permits different probability weighting functions for gains and losses.

Most of the above work has been theoretical in focus with little concern for explaining phenomena beyond the context of urn-type situations such as those originally investigated by Ellsberg (1961). Two exceptions are the models developed by Bewley (1986) and Kahn and Sarin (in press). Building on concepts first advocated by Knight (1921), Bewley has substituted an assumption of inertia (i.e., attraction to the status quo) for the completeness axiom which leads to aversion to uncertainty. Bewley shows that this aversion implies, inter alia, a reluctance to buy or sell insurance under ambiguous circumstances. In a more experimental paper, Kahn and Sarin (in press) operationalize ambiguity by a "second-order" distribution over the uncertain probability which can then be characterized by its standard deviation. They present data concerning gambles for both positive and negative payoffs as well as a number of scenarios in consumer choice that are consistent with the predictions of the Einhorn-Hogarth model.

To summarize, considerable effort has been invested in attempts to capture the effects of ambiguity in models of both probability and choice. Much of this work has been inspired by Ellsberg's (1961) challenge to Savage's (1954) axiomatization of subjective probability and has typically asked how a normatively desirable set of axioms could be amended to account for the way humans react to uncertainty in probability estimates. In distinction to the work presented in this paper, it has not asked *how* people assess uncertainty in the first place.

The model presented in this paper differs from others proposed in the literature in that it is constructed on the basis of *principles of behavior* as opposed to *behavioral principles*. As such, the model carries no guarantee that people whose behavior conforms with the implications of the model will not make judgments or choices that, on mature reflection, they might subsequently recognize as errors. For example, given that the ambiguity function is generally nonlinear in the anchor probabilities, the immediate criticism that can be raised against the present formulation is that it can imply violations of first-order stochastic dominance. When comparing two gambles, these violations are clearly undesirable and a case can be made that when subjects perceive the underlying

structure of such gambles they will not make "mistakes." However, there is good evidence that suggests that people do not always perceive the underlying structure of such problems and that choices can violate the principle of stochastic dominance (see e.g., Goldstein & Einhorn, 1987; Tversky & Kahneman, 1986) in the same way that they have been observed to violate transitivity (Tversky, 1969).

Implications for future work. Although the experimental evidence presented in this paper supports the proposed model, there are aspects that remain untested. For example, the experiments did not test the assumption that the absolute size of payoffs affects the weight given in imagination to values above and below the anchor probability. Moreover, other studies have provided mixed evidence on this point. For example, whereas Hogarth and Kunreuther (1988) found evidence in favor of this hypothesis in a study of pricing decisions made by professional actuaries, data from a choice task involving laboratory gambles did not support the assumption (Hogarth & Einhorn, 1988). It is unclear whether results between these two studies differed because of the nature of the two contexts (gambling versus insurance) or the type of response mode (making a choice versus stating a price). Further investigation is required.

Second, although the results of Experiments 1 and 2 had implications for competitive situations, the different parties to each potential conflict or negotiation did not, in fact, have to deal with each other in a face-to-face manner. It would be interesting to use the present model to examine actual negotiations and compare the effects of interactions involving ambiguous and non-ambiguous information about probabilities.

Finally, in addition to examining effects of ambiguity in different contexts, it would be of interest to develop a model that explains how people cope with the fact that knowledge about payoffs is often also ambiguous. Can this source of uncertainty be handled by an extension of the Einhorn-Hogarth model, or do different principles of behavior apply?

Footnotes

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[1] Schoemaker (1984) has argued that assuming an "optimal" model of a phenomenon is a useful scientific heuristic in the early stages of investigation. However, like metaphors and analogies, optimal models need to give way to more complete accounts of phenomena.

[2] A dictionary definition of the term ambiguity (Webster, 1982) centers on the notion of "having two or more possible meanings" (p.43).

[3] In the Appendix to Einhorn and Hogarth (1985, p. 461), the implications of modeling this in alternative ways are considered. However, an unsatisfactory aspect of this specific formulation noted by Robyn Dawes (personal communication, March 1988) is that for $0 < \beta < 1$, the ambiguity function in equation (4) is always non-montonic in p_A. Such anomalies are, of course, avoided by the more general derivation of the model provided in this paper.

[4] It is should be noted that this result holds independently of the wealth levels of the plaintiff and the defendant, the level of probability on which both agree, and the particular risk-averse utility functions assumed in the analysis (see Gould, 1973).

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Table 1

Experiment 1: Percentages of subjects choosing to settle out of court in different conditions

	Percentages of subjects choosing to settle		
Probability level	.80	.50	(n)
Plaintiffs:			
Non-ambiguous	89	89	(19)
Ambiguous	96	83	(24)
Defendants:			
Non-ambiguous	25	6	(16)
Ambiguous	10	57	(21)

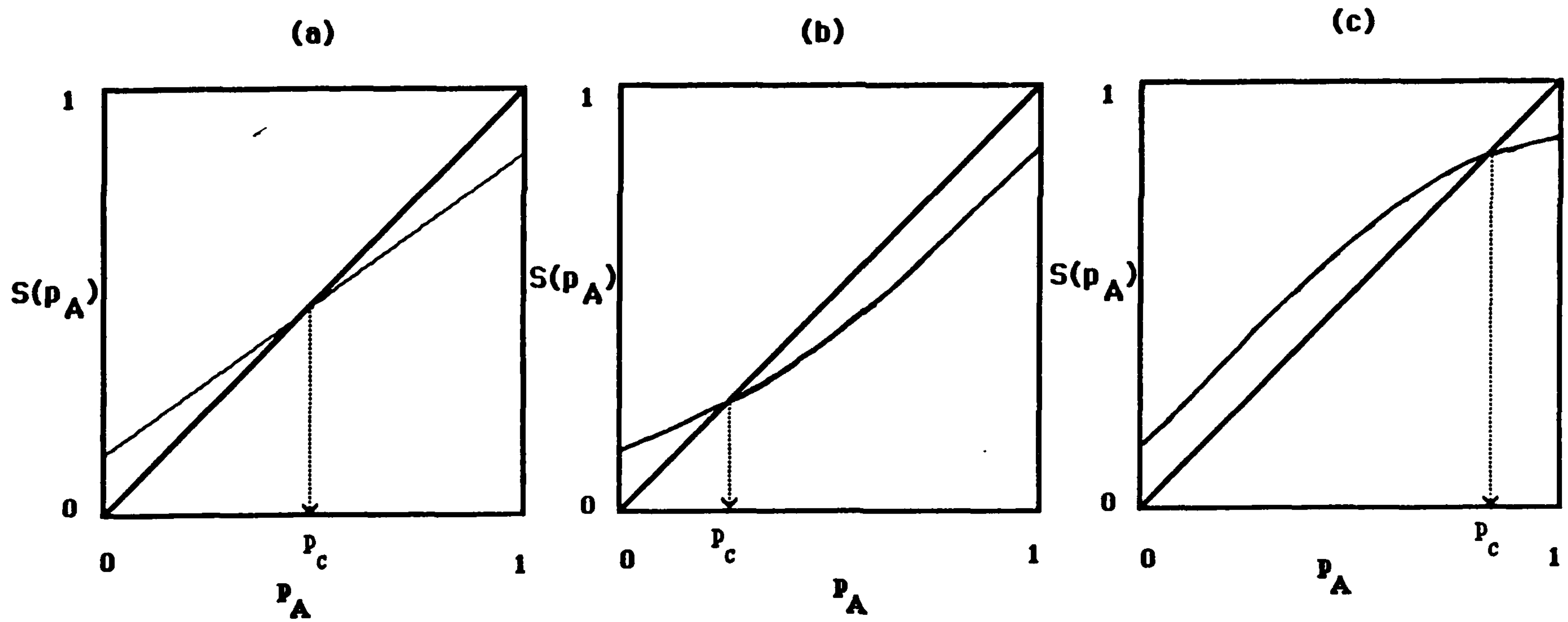
Table 2

Experiment 2: Preferences and discounts of buyers and sellers

	Buyers		Sellers	
	Ambiguous	Non-ambiguous	Ambiguous	Non-ambiguous
	%	%	%	%
Preferences				
For discount	36	68	53	39
warranty	64	32	47	61
	100	100	100	100
n =	36	28	40	33
Stated discounts	$	$	$	$
Minimum for buyers, maximum for sellers				
Medians:	5,000	2,000	1,375	1,000
Means:	4,049	3,011	1,986	1,580

Figure caption

Figure 1: Different ambiguity functions: (a) Values above and below anchor weighted equally in imagination; (b) Values below anchor weighted more heavily in imagination than those above; (c) Values above anchor weighted more heavily in imagination than those below.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